Official Micro Data, Causal Inference and Evidence-Based Policy Making

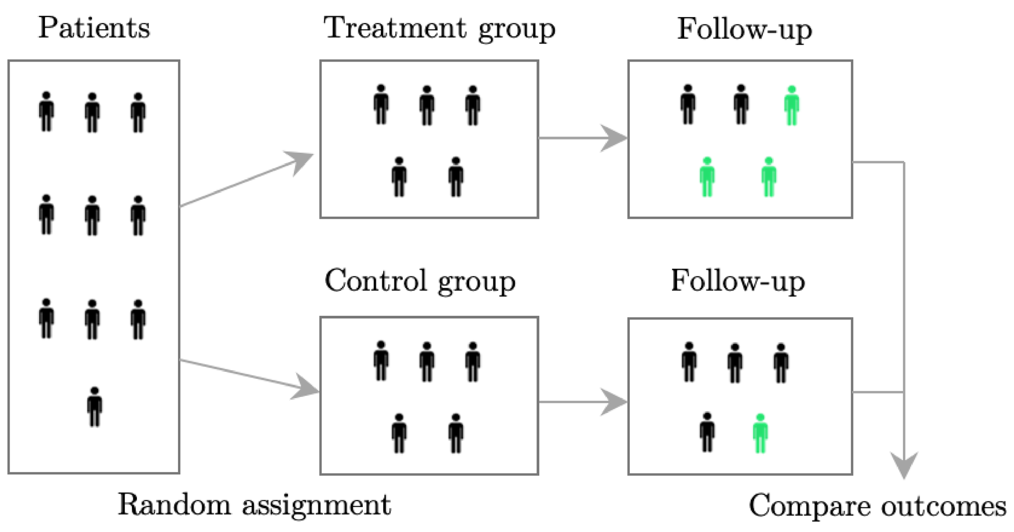
Junchao Zhang
zhang@ism.ac.jp

Why is EBPM important?

- Before EBPM become widespread, policy makers actually do not know whether they are doing the right things.
- However, policy resources are not unlimited. Governments have to allocate resources among different fields to maximize the "economic pie".
- From the cross-sectional perspective, policy decision making implies trade-offs between different objectives/sub-populations.
  - → Efficiency or equality?
  - → Quantity or quality?
  - → Aging or declining birthrates? etc.
- Whether policy interventions have causal effects on people's outcomes? Do these policies improve the economic and social well-being of people?

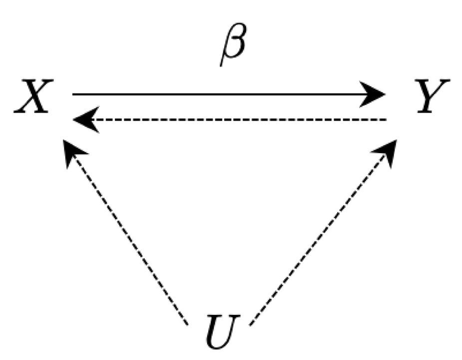
Challenges in policy studies

- In hard sciences, a randomized controlled trial(RCT) is the gold standard for estimating treatment effects.



- We practically meet the following issues in policy studies.
  - → RCT is not allowed because of law and ethics. Randomization is not implemented well.
  - → We can not clearly define treatment and control groups using general survey data.
- Who are exposed to the policy intervention and who are not?

Identification Problem

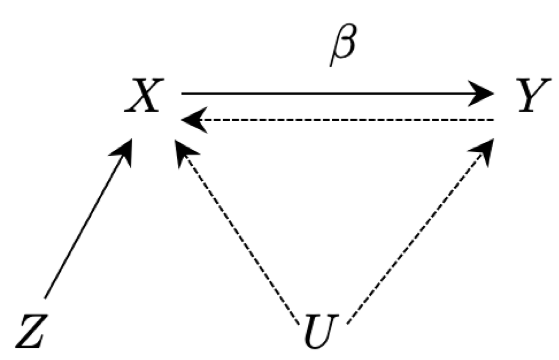


- Using RCT(if randomization is properly implemented), we can simply estimate the average treatment effects by comparing the outcomes between treatment and control groups, or by linear regression.

$$y_i = \beta_0 + \beta_1 x_i + u_i$$

- However, $Cov(x_i, u_i) = 0$ condition is probably not satisfied in most cases of policy studies. Treatment variable x_i is not independent to the error term u_i. With confounder U, β_1 reflects simple correlation rather than causality.

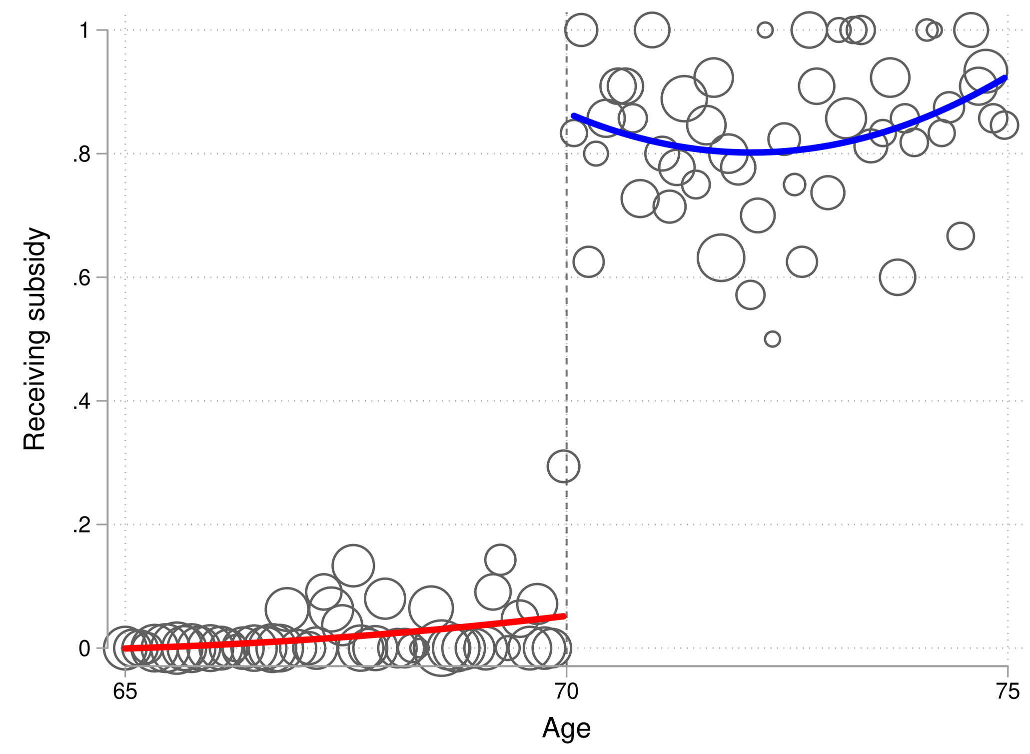
Identification strategy



- Empirically, we need an exogenous variable Z, which can only affect Y through X, to identity the causal parameter β .
- Z should randomly assign people into treatment and control.
- Identification of quasi-experiment design relies on rare events(sudden policy changes, weather events, natural disasters, etc.).
  - → Regression discontinuity design
  - → Difference-in-difference
  - → Instrumental variable, etc.

Why do we need high-quality micro data?

- For instance, regression discontinuity design strongly relies on the continuous running variable, otherwise we can not clearly observe the cutoff point to distinguish treatment and control groups.

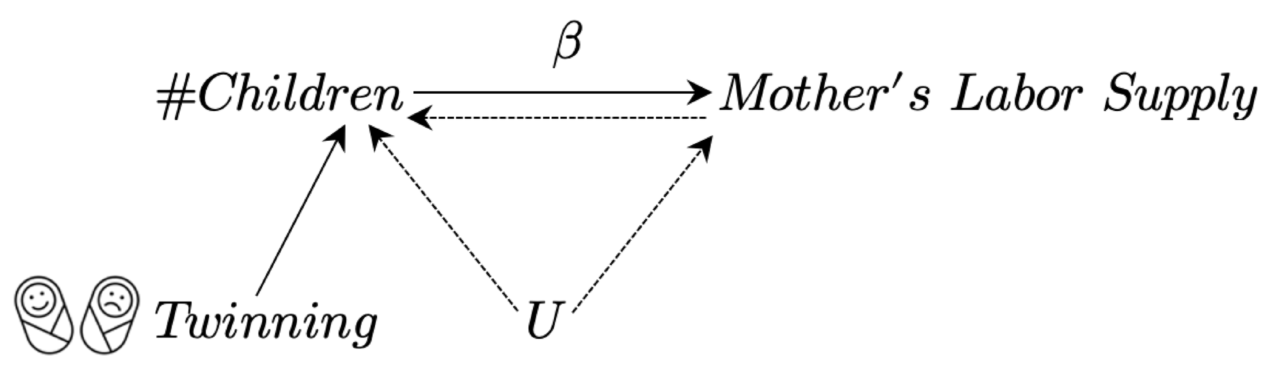


What can we do with offical micro data?

- To estimate causal effects, we need detailed information on Z(e.g. exact date of birth, place of residence, etc.) to define treatment status X. Without Z, we can not tell whether one was exposed to a specific policy intervention.
- Advantages of official micro data
  - → Raw data with detailed information on Z
  - → Large sample size
- With offical micro data, we can simply do
  - → Causal studies without RCT
  - → More sub-sample analysis
  - → GIS analysis, etc.

  that are useful for evidence-based policy making.

Case study: #Children and labor suppy



- Data: Population census of Japan(2005, 2010, and 2015) that covers 100% population (other countries usually offer only 1-5% sample)
- Strategy: We use twinning as the instrument for number of children, which induces exogenous increase in number. Note that this strategy relies on twinning that needs very large sample size.

Comparison of OLS and causal estimates

Table 1. Effects of number of children on maternal labor supply by birth parity and time since last child birth.

	Unconditioned		No more than 3 years		No more than 1 year		No more than 3 months	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Birth parity: 1	-0.003 ***	0.000	-0.005 ***	-0.047 ***	-0.027 ***	-0.031 ***	-0.056 ***	0.004
Birth parity: 2	-0.027 ***	-0.002	0.012 ***	0.004	0.015 ***	0.009	-0.008 ***	-0.001
Birth parity: 3	-0.037 ***	0.050 **	0.002	0.066 **	0.012 **	0.026	0.010	0.072

Notes: All specifications control for age, age squared, education attainment, husband's education attainment, husband's labor force participation, co-residence with elder parents, and prefecture dummies. In all panels, upper bounds on the number of children are not imposed. *** p<0.01, **p<0.05, * p<0.1. Robust standard errors are not reported because of space constraint.

- OLS and causal estimates are quite different in significance and magnitude, which have different implications for policy decision making.
- Negative impacts of children on maternal labor supply are time-varying.
- The impacts also vary across birth parity. First birth has large negative effects, however, second and third birth has very few effect.
- Governments should target who will benefit the most from childcare subsidies.